Preprocessing Using Maximal Autocovariance for Spatio–Temporal Track–Before–Detect Algorithm

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Summary. The detection of local regular patterns and dependent values in heavy noised signal is proposed in this paper. The moving window approach allows computation of the maximal autocovariance of signal. The differences are emphasized using Spatio–Temporal Track–Before–Detect algorithm so tracking such objects is possible. The possibilities of this technique are shown in a few illustrative examples and discussed. The detection of weak signals hidden in the background noise is emphasized.

1 Introduction

Tracking systems are very important in military and civil applications [1, 2]. The most well recognized systems are related to the surveillance. Such systems are applied in the air, space, water surface and underwater surveillance applications. There are many tracking algorithms that are proposed for general or specific applications. Almost all tracking algorithms use conventional processing approach, that is based on the detection and tracking scheme [1, 2]. Tracking systems could be characterized by the number of tracked objects (single or multiple objects) and the number of sensors (single or multiple sensors). The simplest case is related to the single object and single sensor scenario. Larger number of objects needs assignment algorithm that is responsible for the track maintenance. Increased number of sensors needs the proper data fusion.

The position is estimated using the detection algorithm. The detection algorithm is based on the fixed or adaptive threshold. Numerous filtering algorithms are applied for improvement of the detection. Obtained position is processed by the tracking algorithm, so the trajectory is obtained. The tracking algorithm could be very simple if SNR (Signal–to–Noise Ratio) is high. Lower SNR case should be processed by more advanced tracking algorithm, that support motion model of the object. Lower SNR case is characterized by

R.S. Choraś (ed.), *Image Processing and Communications Challenges 5*, Advances in Intelligent Systems and Computing 233,
DOI: 10.1007/978-3-319-01622-1_6,

the multiple detections, so position of the object cannot be estimated using single observation. Multiple observations and processing of them by tracking algorithm allows estimation of the object position for such case. The additional detections (false detections) are suppressed by the gate technique. The gate is assigned to the predicted position of the object. It is possible to estimate (predict) position even if the object detection is not achieved in some measurements due to noise. There are many tracking algorithms like the Benedict–Bordner, Kalman, EKF, Bayes filters [1, 2, 3, 4]. The scheme of conventional approach is shown in Fig. 1.

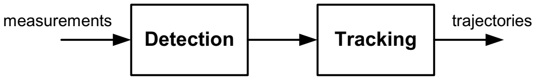

Fig. 1. Detection and Tracking Scheme

The application of the tracking algorithm and the gate technique improves SNR of overall system [1, 5]. SNR could be also very small, e.g. $SNR < 1$. The signal of object is hidden in the noise background in such case. The detection is not possible using conventional techniques at all. The threshold value cannot be correctly selected, and giant amount of false observation may occur, so conventional tracking approach is useless [1, 6, 7].

Low SNR case could be processed using alternative tracking approach that is based on the Track–Before–Detect (TBD) scheme. This approach is based on the opposite processing. All possible trajectories are processed using tracking algorithm. There are many tracking algorithms processed in parallel. There are 100M of tracking filters assuming 1000×1000 image resolution (measurement data) and 100 motion vectors for example. Such processing requirements are fixed and independent on the number of tracked object. The processing cost is fixed even if no one object is in the range. Multiple objects could be processed at the same cost. Most TBD algorithms are multiple object tracking algorithms. The detection of the object is possible after the tracking. The tracking is based on spatial and temporal filtering of signal. It is possible using multidimensional filtering algorithms in some cases. The motion model is related to the motion vectors that define trajectories and cooperation between neighborhood motion vectors. The scheme of TBD approach is shown in Fig. 2.

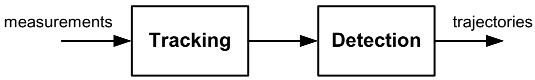

Fig. 2. Track–Before–Detect Scheme

2 Spatio–Temporal Track–Before–Detect Algorithm

The Spatio–Temporal Track–Before–Detect algorithm (ST TBD) is the kind of the multidimensional recursive filter [8]. The following pseudocode shows ST TBD details:

Start
// Initial:

$$P(k=0,s)=0 \tag{1}$$

For $k \geq 1$ and $s \in S$
// Motion Update:

$$P^{-}(k,s)=\int_{S} q_k(s|s_{k-1})P(k-1,s_{k-1})ds_{k-1} \tag{2}$$

// Information Update:

$$P(k,s)=\alpha P^{-}(k,s)+(1-\alpha)X(k) \tag{3}$$

EndFor
End
where:

S	– state space: e.g. 2D position and motion vectors,
s	– state (spatial and velocity components),
k	– time moment,
α	– smoothing coefficient $\alpha \in (0,1)$,
$X(k)$	– measurements,
$P(k,s)$	– estimated value of objects,
$P^{-}(k,s)$	– predicted value of objects,
$q_k(s\|s_{k-1})$	– state transitions (Markov matrix).

There are two formulas in ST TBD. Incoming measurements are processed using the information update formula. It is a kind of the exponential filter with the weight coefficient α. The motion update formula is the predictor. The predicted values of the state space are mixed with incoming measurements using the information update formula. There are two processes that occur in ST TBD. The state space blurring occurs in the motion update, and the state space sharpening occurs in information update formulas. The balance between them is obtained by the selection of the smoothing coefficient.

The state space could be defined using numerous ways. The simplest case occurs for the direct application of the measurement space to the state space. The state space is multidimensional. The ST TBD works as low pass filter so it is well destined to the processing of the positive signals that are disturbed by the zero mean value noise.

The ST TBD have efficient implementations, using for example GPGPUs [9, 10, 11, 12, 13].

3 Preprocessing of Measurement Space Using Maximal Autocovariance

The processing of the positive signal of the object is very important in numerous applications. Weak signals are emphasized by ST TBD and the detection is possible together with the trajectory estimation.

The amplitude modulated signals could be processed using demodulation techniques that are a part of the modified ST TBD [14].

Another kind of the object could be processed after preprocessing. The noise object is characterized using comparison of distribution or distribution parameters. Local variance [15] could be applied for the noise object. Another possibility is direct comparison of distribution histograms. The chi–square statistics [16] could be used for the computation of differences between two distributions [17, 18, 19].

Such approach changes raw signal to the appropriate measurement space [20, 21, 22, 23]. Direct application of ST TBD is not possible, because noise signal has zero mean value, so output of ST TBD for the background and object will be similar.

Autocovariance allows comparison of the original and delayed signal [24]. The signal X is delayed, and the lag is defined as n. The total length of the signal is defined as N.

$$C_{XX}(n) = \frac{1}{N-n} \sum_{i=1+n}^{N} X_i X_{i-n} - (\overline{X}|_{1+n}^{N})(\overline{X}|_{1}^{N-n}) \tag{4}$$

Application of the autocovariance allows testing regularities (e.g. periodicity) of signal [24]. The signal could be any kind. The typical application of the autocovariance is the testing of random generators.

The window approach is applied for the comparison of signals locally. The lag $n = 0$ is omitted, so only positive lags $n > 0$ are considered. The lag $n = 0$ is adequate to the variance computation. The signal is compared with own direct copy, so the output value is positive and high. It is signal variance that is biased. Lack of the relation between signal and specific lag gives zero value, but it is noised value due to small sample size. Periodic signal give high values. Different noise distributions or filtered noise signal also give changes. The object position is not always determined by the highest value and the opposite output is possible. High dependence in the background signal gives high value. The object could be based on low dependence in the own signal, so lower value of autocovariance is obtained. The window approach allows computation of the new measurement for the information update formula (1b).

4 Example Results

4.1 Example: Random Signal – Different Distributions

This example shows results of the Gaussian background noise and the uniform noise related to the object. The result of this example is shown in Fig. 3.

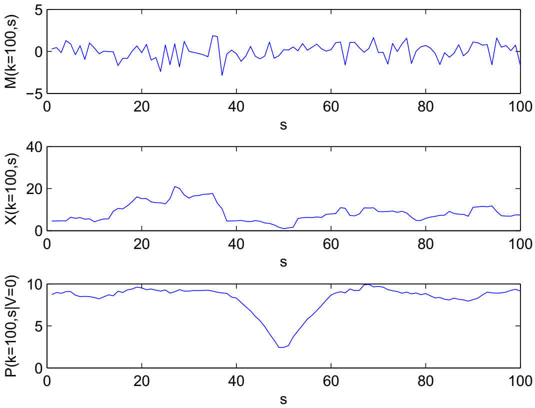

Fig. 3. Output of ST TBD for different noise distributions

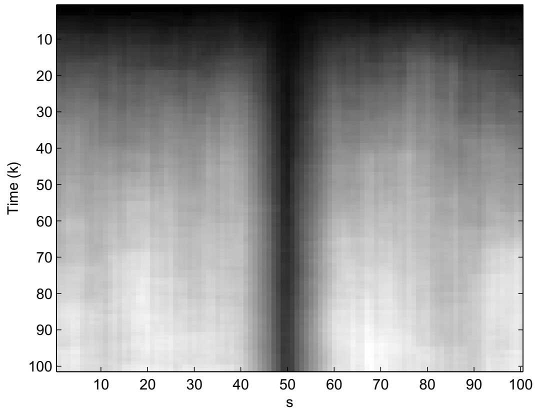

Fig. 4. Example signals after 100 steps: input signal, maximal autocovariance, ST TBD output

This is an example of the case where lower value of maximal autocovariance has lower value (Fig. 4) for the object in comparison to the background. The difference is quite quickly emphasized and is visible after less then 20 step (Fig. 4).

4.2 Example: Periodic Pattern Inside Gaussian Noise

This example shows results of the Gaussian background noise and pattern: (-0.5, 0.5, -0.5, 0.5, -0.5, 0.5, -0.5, 0.5, -0.5). The result of this example is shown in Fig. 5.

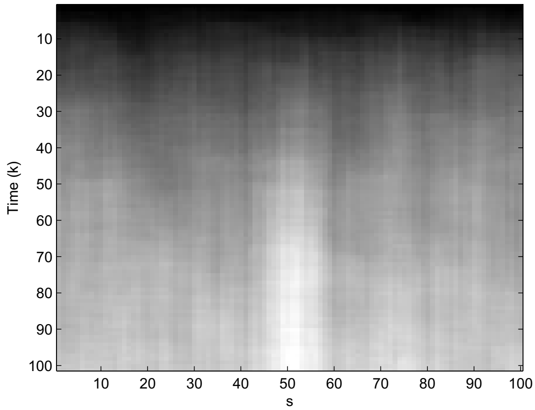

Fig. 5. Output of ST TBD for periodic pattern

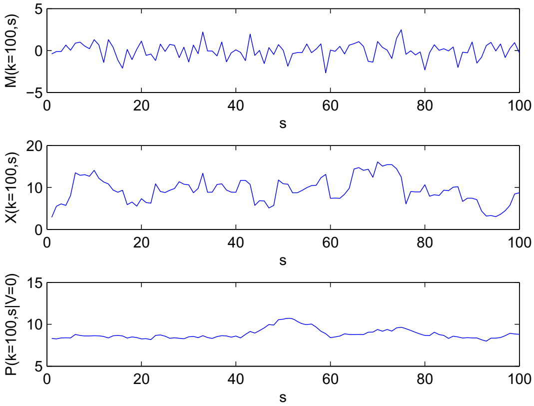

Fig. 6. Example signals after 100 steps: input signal, maximal autocovariance, ST TBD output

This pattern is hidden in the additive background noise, but it is possible to find it. The width of area of detection is extended and blurred due to possibility of the detection even if not all patterns are observed (Fig. 5).

4.3 Example: Filtered Random Signal

This example shows results of the Gaussian background noise and the filtered random signal related to the object. The result of this example is shown in Fig. 7. The signal where, the object is located, is obtained by summation of the Gaussian noise (multiplied by 0.5) and filtered Gaussian noise (also multiplied by 0.5). The signal is filtered using the moving average filter (MA1).

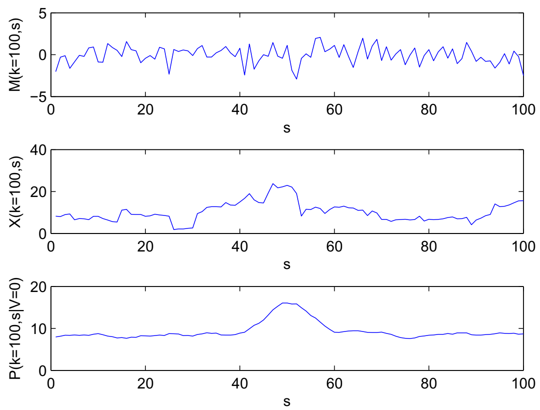

Fig. 7. Output of ST TBD for filtered random signal

This example shows the detection based on the different distributions and samples dependency in the object area. The detection is possible after about 20 processing steps. The detection area is blurred due to partial dependency when the moving window overlaps partially area of the object.

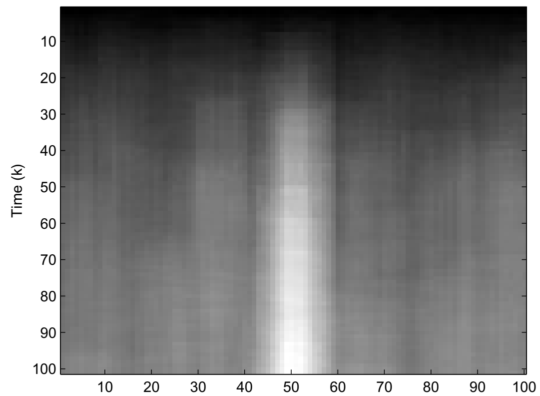

Fig. 8. Example signals after 100 steps: input signal, maximal autocovariance, ST TBD output

5 Discussion and Conclusions

The window size consist of 10 samples, only. Autocovariance is computed for $N-1=9$ lags. It is extremely small data set for the application of the autocovariance.

The obtained results for specific time moment cannot be used for the detection (Fig. 3, Fig. 5, Fig. 7 middle). The detection is possible after/during tracking by filtering of many differences between the background and object signals (Fig. 4, Fig. 6, Fig. 8).

Application of ST TBD allows filtering (e.g. accumulation of the results) so it is possible to distinguish signals after some time steps (Fig. 4, Fig. 6, Fig. 8). The difference is visible after about 20 steps.

ST TBD state space is initialized by zeros, so steady state is achieved after some iterations. It is visible as dark (low value) strip at the beginning of processing (Fig. 4, Fig. 6, Fig. 8).

The state space is multidimensional so it is assumed that object is not moving and the appropriate subspace is shown. The position of the object is fixed around the position 50. The 1D signal is processed but images (2D signals) could be processed also.

The maximal value of autocovariance is processed by ST TBD algorithm. The computation cost of the preprocessing is very small in comparison to ST TBD algorithm. This is important advantage of the proposed algorithm. Efficient implementations using pipeline processing of autocovariance are possible.

The detection of dim objects is important. There is limitation of the proposed algorithm related to the size of the object, that should be large - a few samples (pixels) is the minimum. It is kind of the extended target. Smaller object that occupy single sample cannot be processed using the proposed solution.

The smoothing weight $\alpha = 0.98$ is assumed in all examples. The optimization of this value is possible [16] for improving time response of ST TBD. The delay related to this behavior (similar to delay of the exponential filter) limits application possibilities, where a new object is in the measurement range.

The proposed preprocessing is a valuable tool for the detection specific from the autocovariance point of view differences between the background and noise object signals.

Acknowledgement. This work is supported by the UE EFRR ZPORR project Z/2.32/I/1.3.1/267 /05 "Szczecin University of Technology – Research and Education Center of Modern Multimedia Technologies" (Poland).

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